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Estimates of the social cost of carbon: A review based on meta-analysis

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A R T I C L E I N F O

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A B S T R A C T

There is a great deal of evidence that climate change affects socioeconomic systems. The social cost of carbon (SCC) is calculated by scientists to monetarize the incremental unit of carbon emission and is used to assess climate policies. This study begins with a review of current research on the SCC, followed by a discussion of the choice of models for the SCC. We give a list of advantages of disadvantages of each model and finally use a meta-analysis to evaluate the SCC from published research. The main findings were as follows. (i) Integrated assessment models (IAMs) are often employed to assess the SCC, research on IAMs was started booming in the 1990s and slightly decreased after 2012. (ii) The estimated SCC ranges from −50 to 8752\$/tC (−13.36–2386.91\$/tCO$_2$), with a mean value of 200.57\$/tC (54.70\$/tCO$_2$) and it equals to 112.86\$/tC (30.78\$/tCO$_2$) with a PRTP at 3% in peer-reviewed studies. (iii) The estimated SCC is higher in newer publication year and in peer-reviewed studies, the same trend happens with a higher climatic sensitivity and employing DICE/RICE and PAGE. (iv) The pure rate of time preference (PRTP) is tightly associated with the estimated SCC, and a higher PRTP has a lower estimated SCC. (v) The outliers often appear without realistic scenario setting and in studies have not peer-reviewed.

1. Introduction

Climate change has become one of the greatest worldwide concerning problems. A substantial body of evidence has shown that the climate is all through changing. Frequent extreme weather and climate events have attracted increasing attention in the last few years, owing to the large loss of human life and biodiversity (Easterling et al., 2000). Aside from these extremes, the 5th assessment report from Intergovernmental Panel on Climate (IPCC) has indicated that global land-ocean temperature increased by 0.85 °C from 1880 to 2012 and the average land-ocean temperature of the past three decades indicated this was the hottest period of the last 14 centuries (Change, 2013). IPCC give a clear definition for climate that it narrowly refers to a general or average weather over a long period of time, represented or quantified by the mean and dispersion of temperature, precipitation and wind. In a broader sense, IPCC also states that "climate is the state, including a statistical description of the climate system" (Le Treut et al., 2007). Then, climate change refers to a variability of the climate either because of natural changes or as a consequence of human activities (Planton, 2013). In contrast, there is an incompatibility between the definition of climate change used by scientific research and policy implements. Definition from United Nations Framework Convention on Climate Change (UNFCCC) diagnoses that human activities alters concentration of a certain gas or the atmosphere composition, which gives rise to climate change with the exception of the observed natural variability on climate (Pielke, 2004). Thus, as climate science has been continuing to evolve, climate change is recognized as very likely to be human-induced and is proceeding unprecedentedly over the past thousands of years.

There are obvious evidences and objective basis for rapid climate change. There have been several sources of evidence of the paleoclimate could be found in loess, ice cores, marine sediments, tree rings, coral reefs and calcium carbonate in caves, all of which

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indicate that the climate has fluctuated periodically (Jansen et al., 2007). Today, Earth-orbiting satellites have enabled scientists to collect diverse information of our planet, including observations of the rising sea level, shrinking ice sheets, declining Arctic sea ice, glacial retreat and ocean acidification, all of which indicate that the atmosphere traps more energy than it did 1300 years ago. The IPCC uses sea level, ocean acidification and ice decline as indicators of climate change. Rising sea level is measured as an indicator for global warming because the oceans are receiving additional water from melting ice and are also expanding as they warm. Data from tide gauge and satellite show that global mean sea level rise is about 0.19 m during 1901–2010 (Change, 2013). Another indicator, ice, which covers 10% of Earth's surface, is disappearing rapidly, as shown by the data from Gravity Recovery and Climate Experiment (GRACE) of National Aeronautics and Space Administration (NASA, https://climate.nasa.gov/scientific-consensus/). Ocean acidification is also an indicator to represent climate change because the observed reduction in ocean pH-value results from increasing concentrations of carbon dioxide (CO_2). In addition, ocean acidification poses potential threats to the health of the ocean ecosystems. In summary, there is a great deal of evidence and observations to indicate that our planet is undergoing climate change. However, the extent to which climate change affects the socioeconomic system is not yet fully understood.

One of the central ways that estimates of the marginal damage cost of climate change are essential to assess climate policies is through the use of the social cost of carbon (SCC), defined as the present-value cost of an additional ton of CO_2 emissions (Pearce, 2003). In light of challenges on climate change, strategies and measures for mitigation are primary for policy makers. But do these climate policies work? How are the effects of them? SCC takes an act as a metric to estimate the costs and benefits of a certain regulation policy, and comprehensively quantify the damages of emitting CO_2. As far as its definition concerned, SCC is significance for government and adopted as a basis or guide to tax and implement regulation policies (Pizer et al., 2014). For instance, federal government has made use of the global SCC in the climate negotiations. Furthermore, Environmental Protection Law in China and National Environmental Policy Act in U.S. are all need the vital and orientation information for ministries to measure the costs of CO_2 emissions. Given its uncertainties from assessment approach, ignoring non-market damages of CO_2 emissions, and even controversial assumptions, SCC cannot be labelled as a perfect estimation for climate change damages. However, it is still served as a function of how policy makers aggressively rectify their act and how much damages expected caused by an additional ton of CO_2.

Our research begins with a review of current research on the SCC, followed by a discussion of the choice of models to estimate the SCC. We give a list of advantages of disadvantages of each model and finally apply a meta-analysis method to evaluate the SCC based on published research.

2. Theoretical background

2.1. Physical mechanism of the greenhouse effect

In the process of estimating SCC, the interaction among climate, CO_2 concentration in atmosphere and CO_2 emission from human activities works as the essential scientific basis. On account of the large spatial and temporal variability of the climate system, scientific observations indicate that climate system is evolving under the influence of its own internal dynamics and the changes of its external forcing (Steffen et al., 2006). In the solar system, the sun provides energy to the Earth through radiation and, to balance the incoming energy, our planet generally must transmit the same amount of energy in the form of waves or particles back into space. However, in this physical mechanism, the climate system response to solar radiation as a cover for the Earth by means of substance and energy transmission. Approximately 30% of the incoming sunlight is reflected back to space at the top of the atmosphere, roughly two-thirds of which is due to aerosols and clouds in the atmosphere, the remaining one-third of reflectivity is due to light-colored areas of the Earth's surface such as snow and ice (Le Treut et al., 2007). Those remaining energy is taken in completely by the Earth's surface and atmosphere. Our planet continues to radiate to emit energy again for balance, but the presence of greenhouse gas (GHG), which is one of the crucial components of the climate system, acts as a blanket by trapping the radiation from Earth towards space. Scientists introduced a term, radiation forcing, as a measure of the net change in the energy balance of the Earth system in response to external perturbation (Stocker et al., 2014). Thus, the energy balance of our planet could be changed in three basic ways theoretically: the first one is to change the incoming energy from the sun; the second is to alter the albedo of aerosols, clouds and the surface of our planet; the final one is to change the GHG concentrations in the atmosphere.

GHG act as a shelter response to the incoming radiation from solar system and the emission energy from the Earth's surface. These long atmospheric lifetime gases consist of water vapor, CO_2, methane (CH_4), nitrous oxide (N_2O), ozone (O_3) and a small amount of chlorofluorocarbons (Meinshausen et al., 2011a). GHG is also one of the fundamental causes of greenhouse effect for absorbing and emitting infrared radiation. However, different atmosphere gases contribute to the greenhouse effect with varying degrees, whose impact is 60% from water vapor, 25% from CO_2, and the rest from remaining gases (Karl et al., 2003). Thus, human activities have played a role in climate change by discharging GHG and changing land use to alter the components and GHG concentration in atmosphere. The other way round, climate change has also had a compound influence on the human socioeconomic system measured by SCC (Adger et al., 2013). As aforesaid, the whole process of greenhouse effect is complex and changeable, then one of the main uncertainties of SCC is that the estimation has over-simplified this physical mechanism.

2.2. Impacts of climate change on the socioeconomic system

Climate change, and its impacts on the socioeconomic system, is one of the major issues that the world will have to manage in the twenty-first century (Stocker et al., 2014). Over the past recent decades, these changes have become more visible in the form of frequent changes on weather pattern, leading to severe drought or floods in some regions, which in turn threaten the economy system, natural and man-made ecosystems and even human survival. Agriculture is a sensitive and vulnerable sector influenced by global warming and extreme weather conditions, particularly for crop growth and food security (Berry et al., 2006). As global warming is believed to do harm to rain-fed crops but friendly to irrigated plant species, rising temperature may produce either positive or negative effects on crop yield. Piao et al. (2010) showed that rice yields in the northeast of China saw a 4.5%–14.6% increase per °C in the course of nighttime warming during 1951–2002, while daytime warmer are likely to have negative impact on wheat yield with a 6%–20% decrease per °C. Calzadilla et al. (2013) identified that the productivity of crops was determined by many interactive processes, but precipitation patterns altered by global warming were the main climatic processes for crop growth. However, Wu et al. (2014) believed that the pros of climate change outweigh the cons, for instance, the uneven distribution of water resources caused by temporal and spatial variation of precipitation pattern was one of

the main reasons for intensified droughts and floods, which was devastating for plants.

Previous studies have also indicated that climate variability has limited direct effects on secondary and tertiary industry, and these impacts are often produced indirectly by affecting resource-based sectors, such as agriculture and forestry (O'Brien et al., 2000). For example, extreme events such as earthquakes can ruin forest or brushwood and weaken the provision of timber for the furniture market. Moreover, the price of agricultural products might vary with climatic variability and then pose a threat to the manufacturing industry. In addition, the potential growing period has been extended by regional warming, for example, the rising temperature has also enabled a significant northward shift of crops planting in Heilongjiang province. This shift would pose challenges for the availability of food and also promote transportation costs for partial regions (Meng et al., 2014). The socioeconomic system is also vulnerable to the pressure of climatic changes. For instance, transportation will be hindered if there is a heavy rainstorm or typhoon. Sectors such as tourism that are heavily relied on smooth traffic then may be influenced by hazards. Furthermore, Watts et al. (2015) also indicated that heatwaves directly affect human health and land use change affecting food supply is also associated with human nutrition. Hajat et al. (2014) concluded that public health measured by mortality rates, which associated with exposure to surrounding temperature. Moreover, evidence in recent decades has indicated that warming could be related to negative health effects, including heat-related disorders, such as heat stress, respiratory disorders and infectious diseases (Patz et al., 2014). The Food and Agriculture Organization (FAO) found that 793 million people suffered from chronic hunger and the cost of malnutrition was about 3.5 million dollars per year (http://www.fao.org/nutrition/en/). In brief, the linkages among social dynamics, economic development and climatic variability have been proved by many studies.

2.3. Development of economics of climate change

Potential impacts of climate change are usually analyzed or assessed in a view of standard neoclassical welfare economics (Foley et al., 2013). In 1896, a Swedish scientist established a theoretical concept for global warming on the condition that a lot of the scholars declared implausible. In the 1950s, a few scientists discovered global warming and considered it to be a possible future issue. In 2001, thousands of experts were mobilized to attach importance to global warming, and this measurable phenomenon was emphasized that it would affect the weather pattern and even would probably get much worse under the influence of human activities (Weart, 2008). With the deepening of understanding of climate change, scientists responded to this risk that would affect our human wellbeing and the evolution of human society by conducting empirical studies in terms of economy. In the 1980s, Nordhaus started to take climate change as one of the global commons to analyze the problem by using economic methods. Subsequently, the term "economics of climate change" was formally put forward with the explosion of research on climate change. However, the term is not as clearly defined as climate or climate change so far, the research on economics of climate change have mainly focused on modelling CO_2 emissions from economic growth, examining the economics of technological options, calculating SCC, and exploring tax for CO_2 emissions, investigating markets or industrial structures (Stern, 2006).

Current research on the economics of climate change is mainly concentrated on three topics. As shown in Fig. 1, we randomly filtered 150 pieces of literature from numerous research studies in a search for the keyword "economics of climate change" at Web of

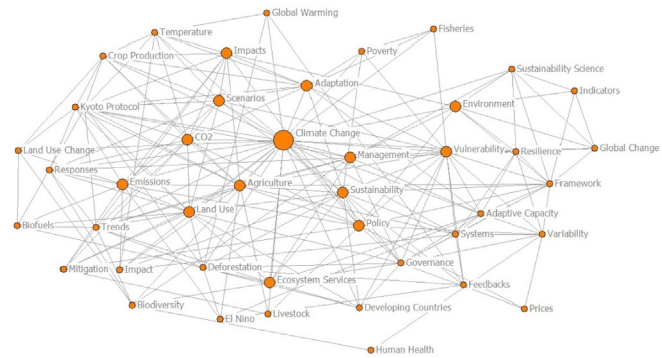


Fig. 1. Network of keywords in search of "economics of climate change" at Web of Science.

Science. The first topic refers to the driving mechanism of climate change. Stern (2006) claimed that energy use, agriculture and deforestation were the three big contributors for GHG emissions. Thus, in Fig. 1, "climate change" is closely related to "CO_2", "agriculture" and "deforestation". The second is the impacts of climate change. Climate change exerts wide-ranging influences on natural flows and the economy, including agriculture, transportation, tourism, human health and so on (Piao et al., 2010). In addition, quantifying and modelling the implications of the integrated impacts has been widely discussed. The third branch is on climate change mitigation and adaptation. This includes how to adjust ecosystem and socioeconomic systems in response to the changes caused by catastrophic events or warming, and how to alleviate adverse impacts of change or take advantages of new opportunities of climate change. Governors advocated reducing carbon by using clean energy and developing carbon capture and storage technology (Liu et al., 2013). Stern (2006) also indicated that adaptation requires economic planning or policies such as a carbon tariff to alleviate pressure on carbon reduction. Although the economic benefits of policies to reduce carbon emissions remain unclear, the studies identified that many economic sectors and some aspects of quality of life are sensitive to climate change.

3. Estimates of SCC

3.1. SCC

SCC is an important concept and also a crucial tool for economic analysis and implementing climate policies (Nordhaus, 2014). It is defined by many studies as the economic cost of an additional ton of CO_2 emitted to the atmosphere or the value of damages associated with an incremental unit of carbon emission (Dietz, 2012). In 2010, the U.S. federal government's Interagency Working Group (IWG) initially aimed to use SCC to monetarize the external cost of carbon emission and assess the climate and energy regulations (Dayaratna et al., 2017). In the existing studies, there are a set of methodologies to estimate SCC, which attempts to be classified into two alternative approaches both with high uncertainties, cost-benefits analysis and marginal cost method. IWG has produced an updated SCC by incorporating a probability density function and other minor revisions to the underlying three Integrated assessment models (IAMs), namely FUND, DICE and PAGE (Forest, 2017). IAMs are one of the main kinds of model to realized cost-benefits analysis to calculate the SCC through simulating the path of climate change. Indeed, most industry groups have been against the idea of implementing a SCC, although it is still effective as a basis to improve the environmental efficiency for companies. As stated in the current researches, the arguments against SCC are mainly

focused on its uncertainties from estimation approach or the accuracy of the number itself. As shown in Table 1, the core formulas to calculate SCC in a part of IAMs are summarized. In addition to the oversimplified translation of CO_2 emission to concentration of carbon and climate impacts, the optimal estimation of SCC strongly depends on the damage function in IAMs, and key parameters (e.g. climatic sensitivity, intergenerational discount rate and regional equity) exert a tremendous influence on the final estimation results of SCC (Tol, 2008; Pizer et al., 2014). Furthermore, most of the researches excluded non-market damages, those impacts like loss of the value of biodiversity. All these uncertainties cause the value of SCC debatable. As thus, there is a substantial difference among the prices of carbon released by distinct organizations. For instance, IWG's estimation to guide U.S. policymakers has reported that a mean SCC for the year 2020 was $37 based on DICE at a 3% discount rate. In addition, the report also showed that the 95th percentile of SCC estimated across all three models at a discount rate of 3% was $72.8 (Newbold et al., 2013). Tol (2008) estimated the SCC based on 211 estimates from 47 studies, and found that the estimated SCC was higher with a lower discount rate and there was a downward trend in the economic impact of climate. The establishment of the conceptual basis of SCC signals that the society is willing to pay to avoid future damage caused by an additional ton of carbon emissions. For an optimal climate or energy policy, the market-price should be equal to the marginal abatement cost if the carbon market covers all emissions and is competitive. In principle, this process is often used to set the goal in IAMs for policy assessment.

3.2. Models used for estimating SCC

The IAMs represent a common tool or general theoretical framework to assess the cost and benefits strategies over time taking SCC as quantitative criteria to choose optimal climatic policies. This tool presents the cause and effect chain or the "path" of climate change, covering the socioeconomic system that causes emissions, the interaction between these emissions and GHG concentration in atmosphere, changes of temperature and other climatic indicators induced by the increased concentrations, and the damages on economy caused by this varying climate (Patt et al., 2010). As shown in Fig. 2, a full IAM combines a climate change module, hazard module, energy model and socioeconomic module to determine the SCC. Weyant et al. (1996) concluded that IAMs have served three purposes in principle. Firstly, it is to assess potential responses to climatic variability by modelling physical, economic and even ecological processes to project the consequences of warming and of a particular climate policy. Second, IAMs promote a broad view of the climate issue by providing a coherent systematic framework through which to structure present knowledge, and offer a consistent description of current uncertainties on related research, permitting emission space identification and prioritization of measures and policies that are most significant in practice. Third, IAMs can be utilized to address the most fundamental policy issues about global climate change, how significant is it relative to other matters of human concern? It is complex for IAMs to include different principles within the framework, and most IAMs include only a simplified climatic module and carbon cycle module to ensure that the model is tractable. However, with the possibility of simplifications leading to imprecision (one of uncertainties of IAMs) on projecting impacts of climate change and costs of mitigation, the results from IAMs often have low credibility, meanwhile the quality or the practicability of policy advice is correspondingly poor.

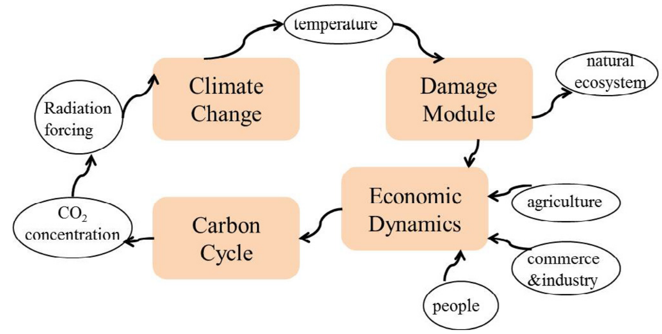


Fig. 2. Basic framework of Integrated Assessment Model.

IAMs was initially developed from "Club of Rome" for the analysis on environmental issues in 1970s, such as environmental pollution, shortage of natural resources, etc. They have been used to examine four basic factors (land, water, environment and ecology) that ultimately determined limit growth (Meadows et al., 1972). IAMs characterized in simultaneous consideration of integration of ecological and economic problems (Wei et al., 2013). Initially, most IAMs described climatic modules with a hypothesis that climate change was coherent globally or zonally and it was also assumed to be identical at a seasonal or annual resolution. Afterwards, the developers of IAMs committed to embrace each aspect of

Table 1
Functions to estimate social cost of carbon from different studies.

Authors	Equations for SCC
Chris Hope, David Newbery	$\frac{CC}{SCC} = \frac{cov(D_r, Y_{r0})/Y_{w0} + D}{cov(D_r, n_r) + D}$
Stephen Newbold, Charles Griffiths, Chris Moore, Ann Wolverton, and Elizabeth Kopits	$SCC = \frac{dC_t}{dX_t} = \frac{\partial E[W_0]/\partial X_t}{\partial E[W_0]/\partial C_t}$
William Nordhaus	$SCC = \frac{\partial W}{\partial E(t)} / \frac{\partial W}{\partial C(t)}$
David Anthoff Richard S.J. Tola and Gary W. Yohef	$SCC_r = \sum \frac{I_{tr}(\sum E_s + \delta_s) - I_{tr}(\sum E_s)}{\prod 1 + \rho + \eta g_{sr}} / \sum \delta_t$
Anthoff, David; Rose, Steven; Tol, Richard S. J.; Waldhoff, Stephanie	$SCC_r = \sum \frac{D_{trs}(E_{1950} + \delta_{1950}, \ldots, E_t + \delta_t) - D_{trs}(E_{1950}, \ldots, E_t)}{\prod 1 + \rho + \eta g_{sr}}$
Anthoff, David; Tol, Richard S. J.	$SCC_r = \frac{1}{\frac{\partial U}{\partial C}} \frac{1}{\sum \delta} \sum_r \sum_t \frac{dC \frac{\partial U}{\partial C}}{\prod 1 + \rho}$
Elisabeth Moyer, Mark D. Woolley, Michael J. Glottr, David A. Weisbach	$SCC = \sum \frac{(C_b - C_1)_t}{(1 + r)^t}$
Inge van den Bijgaart, Reyer Gerlagh, Luuk Korsten, Matti Liski	$SCC = \Delta\theta(c)Y(t)W(\sigma, \gamma)$

environmental and ecological changes, especially dynamic interactions and feedback mechanisms between society and the environment, and attempted to include or even assess patterns of climate change deduced from complex experiments. Accumulatively, these efforts on investigating IAMs often resulted in the redundancy of the components or modules within IAMs, involving reports of changes in CO_2 or GHG emissions, shifts in global average temperature, estimation of impacts of climate dynamics on society, cost-benefit analysis of damages attributing to climate change and decision support on the focus of their study (Wei et al., 2015). Weyant et al. (1996) stated that the first IAM for an environmental problem was named CIAP developed in 1974. Then, the late 1970s has witnessed the evolvement of formally modelled integrated assessments of energy policy. Models such as World 3 were developed and have been further enhanced by coupling ecological, economic and physical processes. Afterwards, the RAINS model was generated for extracting essential information and controlling European-wide acid rain in the early 1980s. In this process, the integrated approach was explored and gradually adopted to seek for solutions of a great deal of climatic issues. It was also a vintage decade for the studies on assessment of SCC (Rotmans et al., 1999). Until the early 1990s, a number of formal IAMs for climatic issues were appeared, starting with models like IMAGE 1.0 and ESCAPE in a simplified form involving the aspects of climate, economy and ecosystems (Goodess et al., 2003). With the deep understanding on climate change, MAGICC, which was the prime reduced-complexity model often used by the IPCC, was jointly exploited by National Centre for Atmospheric Research, University of Adelaide and Manchester Metropolitan University in the late 1980s and early 1990s. Combination between computable general equilibrium (CGE) model and climate model is a potential method to solve this issue (Mi et al., 2017). Afterwards, more modules such as energy flow were introduced into the framework for integrated assessment, such as CETA, DNE21, E3MG, and GCAM. By 2005, research on IAMs was in a sharp rise because of the policymaking requirement for climate change mitigation.

Scientists categorized these IAMs based on their internal mechanism, purposes and coverage, etc. Dowlatabadi (1995) divided IAMs into general equilibrium models, optimization models and simulation models considering the economic portion of IAMs, and also three categories of models for policy evaluation were provided: cost-effectiveness, cost-impact and cost-benefit. Soon after, Dowlatabadi and Rotmans (1998) give another possible classification of IAMs, macroeconomic-oriented models and biosphere-oriented models, on the basis of a framework-based description of a problem. Paralleled with Dowlatabadi, Weyant et al. (1996) categorized IAMs into policy optimization models and policy evaluation models in the light of their internal settings. Rotmans et al. (1999) also stated that in hence IAMs put emphasis on hybrid models containing both economy and dynamic environment. Stanton et al. (2009) elaborately divided the IAMs listed in their research into five categories based on the perspective of climatic analysis, namely welfare maximization models, general equilibrium models, partial equilibrium models, simulation models and cost minimization models. In addition, with the description of the structure of IAMs based on related literature, most IAMs consist of modules and simulate impacts, whereas the others include multiple models, such as CLIMPACTS and DEMETER (Table 1).

We searched for research on different categories of IAMs on Web of Science and Google Scholar separately, and the summary (Fig. 3 and Fig. 4) indicates that scientists have paid more attention to IAMs since 2009, especially the welfare maximization models and general equilibrium models. However, the amount of published research on IAMs has slightly decreased since then as increasing numbers of scientists have realized that the simulation results were not accurate.

3.3. Comparison of different IAMs

A total of 36 IAMs are shown in Table 2 and their structures, characteristics and applications are summarized based on peer-reviewed literature and their official website. Most of these models take the world as a whole as the study area and thus international trade information can be excluded from the mechanisms. However, 15 IAMs are regional or multi-regional models and introduce the regional features into their mechanisms. These regional models, such as AIM, CLIMPACTS and IGEM, are all specific for a nation or a region and were developed based on the existing IAMs. Multi-regional models, such as ESCAPE, FUND, GRAPE, IMACLIM-R, MARIA, MESSAGE, PAGE and RAINS, are divided the world into the study area and the rest of the world.

However, IAMs have been continuing doubted and even fiercely criticized by an accumulated researches for their simplification of the internal mechanism of climate, economic system and environment, or even irrational assumptions, such as homogenous preferences, rational expectations, inter-temporal optimization, market clearing and general equilibrium effects (Pindyck, 2013). For instance, policy optimization models achieve an efficient solution by maximizing the global welfare. That is, policy optimization models provide a description of four components (the climate change module, carbon cycle, damage module and socioeconomic module), omitting regional and temporal equity (Kelly et al., 1999). Moreover, most IAMs simulate the damage with an assumption that CO_2 is evenly distributed, but with the findings that CO_2 concentration varies among countries and seasons, the key parameters that are identical in the climate change module of all regions reduced the accuracy of the results and strengthen the interregional inequity. Furthermore, nearly all the IAMs establish the socioeconomic system based on market equilibrium and thus they leave the irrational factors out of consideration, such as cultural differences and habits. However, Gerst et al. (2013) included these irrational factors in the model by extending the IAM framework with agent-based modelling to describe the economic issues in a more general way. Policy evaluation models consider the impact of a certain policy option and its evaluation process to be more like a black box. They thus attempt to provide a thorough description of the complex and long-term dynamics of the climate system and poorly represent the socioeconomic system (Weyant et al., 1996). The forms of different modules and their uncertainties are listed in Table 3.

In summary, IAMs have been criticized for their uncertainties on the equilibrium climate sensitivity parameter, imperfection of damage functions, the rough handling of catastrophic events, and the identification of discount rate. These uncertainties will continue to cause considerable variation in the estimates of SCC.

4. Meta-analysis on the estimated SCC

SCC refers to the external costs of carbon emission. In retrospect, carbon emissions contribute to the GHG concentrations, which affect radiative forcing and give rise to higher global temperature. In turn, the higher temperature changes the climatic system, causing benefits and damage to society. The traditional countermeasure to address the externality of climate change is to define a price for carbon emissions, which is tantamount to the social marginal damage (Greenstone et al., 2013; Metcalf et al., 2017). In the current study, meta-analysis was used to obtain the SCC from the currently available research. Meta-analysis is a statistical approach to address a set of related research hypotheses by

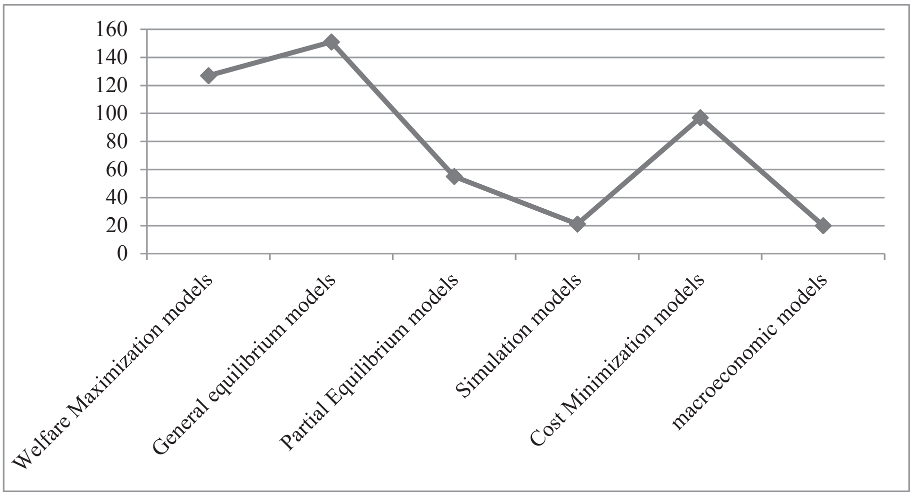


Fig. 3. Numbers of researches of different IAMs from Web of Science.

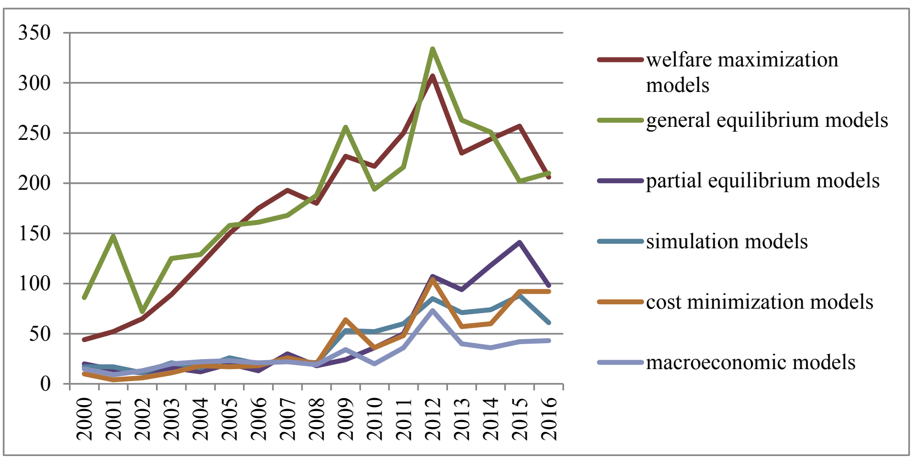


Fig. 4. Numbers of researches of different IAMs from Google Scholar.

integrating the results of existing studies and has been widely used in the medical and social sciences (Kuik et al., 2009). It was originally utilized to prove that vaccination against intestinal fever is ineffective by Karl Pearson in 1904 based on the data collected from related research (Mann, 1994). This technique has evolved into multiple areas and there are now several studies available on SCC. We propose to examine whether estimates of the SCC are dependent on key parameters and characteristics of models. For our application, a meta-regression is applied as follows:

$$y_i = x_i\beta_i + \varepsilon_i \tag{1}$$

where y_i is SCC, the coefficient β_i reflects how the independent variables x_i affect the SCC.

4.1. The dataset for meta-analysis

A total of 578 estimates of SCC were gathered from 58 studies. All the studies are selected by searching "social cost of carbon" in Google Scholar dataset. 172 literature are originally screened due to the key word is included in the text, but 58 studies are recorded as samples in our meta-analysis. According to the studies from Tol (2008), we have summarized some basic characters which may affect the final estimation of SCC in each study.

(*i*) Basically, that the studies are peer-reviewed can be firstly labelled as PR, then samples for meta-analysis were classified into two groups, one was peer-reviewed and another was not.
(*ii*) The second characteristic for these studies is whether the reported SCC is originally estimated based on IAMs. Many studies have independently conducted their research and estimated SCC by using a certain IAM, while there are still some other studies obtained or used SCC from previous studies, independent estimation can be labelled as IE.
(*iii*) The third feature that might have an influence on the estimated SCC is the scenarios set in the studies. In the collected researches, a few studies estimated SCC based on the entirely unrealistic scenario settings, while most studies were conducted based on internally or mechanism consistent scenarios labelled as RS.
(*iv*) Treatment of uncertainty is also one of the key information extracted in all samples. A part of the studies have adopted declining discount rate by considering the climate change prevention, and recently Monto Carlo method has been

Table 2
Basic information of 36 IAMs.

Model	Type of IAMs	Developers	Geographic scale	Modules	Deviants	References
AIM (Asia-Pacific Integrated Model)	CGE model, policy evaluation	Kyoto University[1], Mizuho Information Research Institute[2]	Asian Pacific region (21 regions[①])	GHG emission/global warming impact/ GHG cycle and climate model	AIM/ Dynamic Global; AIM/Trend; AIM/Enduse	Matsuoka et al. (1995)
ASF (Atmospheric Stabilization Framework)	–	EPA	9 regions[②]	GHG emission/agriculture/CFC module/ tropical forest	AIM	Leggett et al. (1992)
CETA (Carbon Emission Trajectory Assessment)	policy evaluation	Peck and Teisberg	6 regions[①]	Economic growth/energy consumption/ energy technology choice/global warming/ global warming costs	CETA-M; CETA-R	Peck and Teisberg (1992)
CLIMPACTS	computer-based syste	New Zealand Foundation for Research, Science and Technology (FRST)	New Zealand	It is a computer-based syste integrated MAGICC, GCM and crop-weather model together	SimCLIM	Peck and Teisberg (1992)
DEMETER (Development of a European Multi-model Ensemble Forecast System for Seasonal to Inter-annual Climate Prediction)	multi-model ensemble forecast system	European Union Vth Framework Environment Programme	Global	7 global coupled ocean-atmosphere models: CERFACS/ECMWF/INGV/LODYC/ Météo-France/Met Office/MPI	DEMETER-1CCS	Warrick et al. (2001)
DICE (Dynamic Integrated model of Climate and the Economy)	policy optimization	William Nordhaus	Global	Emissions/concentrations/climate change/ damages/emissions controls	RICE/ ENTICE/ MARIA	Nordhaus and Sztorc (2013)
DNE21 (Dynamic New Earth 21)	policy evaluation	Yokohama National University	10 regions[①]	energy system/macroeconomic/climate change model	LDNE21	Fujii and Yamaji (1998)
DEARS (Dynamic Energy-economy Assessment model with multi-Regions and multi-Sectors)	policy evaluation	Research Institute of Innovative Technology for the Earth; Ritsumeikan University, Japan	18 regions[①]	18 industry sectors/7 primary energy sources/4 energy categories	THERESIA	Homma (2013)
ENTICE (Endogenous technological change in the DICE model of global warming)	policy optimization	National bureau of economic research	Global	Energy system/macroeconomic system/ concentrations/climate change/damages	ENTICE-BR	Popp (2004)
ESCAPE (Evaluation of Strategies to address Climate change by Adapting to and Preventing Emissions)	policy evaluation	RIVM[3], Oxford University, Dutch Institute for Environment and Public Health, the Climatic Research Unit of East Anglia	4 regions[①]	Emissions/two integrated climate modules/damages		Loulou (2008)
E3MG (Energy-Environment-Economy Model of the Globe)	policy evaluation	Cambridge Econometrics	20 regions[①]	Economy/energy system		Dagoumas and Barker (2010)
FUND (Framework for Uncertainty, Negotiation and Distribution)	policy optimization	Richard S. J. Tol	16 regions[①]	climate change/population/economy/GHG emissions/carbon cycle/damages		Tol (1997)
G-CUBED/MSG3 (Global General Equilibrium Growth Model)	policy evaluation	Brookings Institution, Australian National University, The University of Texas, the Environmental Protection Agency	8 regions[①]	macroeconometric models/computable general equilibrium models	Asia-Pacific G-Cubed Model	McKibbin and Wilcoxen (1999)
GCAM (Global Change Assessment Model)	policy evaluation	Pacific Northwest National Laboratory, University of Maryland	Global	technology-rich representations of the economy/energy/climate model/land use and water	MiniCAM, GCAM-IIM	Edmonds et al. (1997)
GIM (Global Impact Model)	policy evaluation	Yale School of Forestry and Environmental Studies; Middlebury College; University of Illinois	Global	Climate/sectoral features/climate response functions for each sector		Mendelsohn and Williams (2004)
GRAPE (Global Relationship Assessment to Protect the Environment)	policy evaluation	Institute for Applied Energy, Japan	11 regions[②]	Energy/climate/land use/ macroeconomics/environmental impacts		Kurosawa (2004)
GTEM (Global Trade and Environmental Model)	policy evaluation	ABARE[4]	45 regions[①]	Megabare model/GTAP model		Tulpulé et al. (1999)
ICAM (Integrated Climate Assessment Model)	policy evaluation	Carnegie Mellon University	Global	Energy system/GNP/market impact of climate change	ICAM-1; ICAM-2; etc	Dowlatabadi (1998)
IGEM (Inter-temporal General Equilibrium Model)	policy evaluation	Harvard University; The Maxwell School, Syracuse University	U.S	a dynamic model of the U.S. economy which describes growth due to capital accumulation, technical change and population change		Jorgenson et al. (2018)
IGSM (Integrated Global Systems Model)	policy evaluation	Massachusetts Institute of Technology (MIT)	37 regions[①]	Economic Projection and Policy Analysis (EPPA) model/MIT Earth System model (MESM).	IGSM-WRS; IGSM-CAM	Reilly (2013)
IMAGE (Integrated Model to Assess the Greenhouse Effect)	policy evaluation	RIVM and The Dutch National Institute for Public Health	Global	Energy system/land use/plant growth and carbon modelling/carbon and water cycle (LPJmL)/agro-economic model (MAGNET)/ policy and impact models		Rotmans (2012)
IMACLIM-R (IMpact Assessment of CLIMate policies- Recursive version)	policy evaluation	CIRED[5]	5 regions[②]	a dynamic recursive computable general equilibrium model of the world economy	IMACLIM-S	Crassous et al. (2006)
			Global	Dynamic economic model/climate model		

Table 2 (*continued*)

Model	Type of IAMs	Developers	Geographic scale	Modules	Deviants	References
MADIAM (Multi-actor Dynamic Integrated Assessment Model)	policy evaluation	Global Climate Forum (Klaus Hasselmann and Dmitry V. Kovalevsky)			SDIAM; SDEM	Weber and Hasselmann (2005)
MAGICC (Model for the Assessment of Greenhouse gas Induced Climate Change)	policy evaluation	National Centre for Atmospheric Research, Boulder; University of Adelaide; and Manchester Metropolitan University	Global	Gas-cycle model/climate model		Meinshausen et al. (2011b)
MARIA (Multiregional Approach for Resource and Industry Allocation)	policy evaluation	Department of Industrial Administration, Faculty of Science and Technology, Science University of Tokyo (S. Moil)	3 regions①	Global warming subsystem/economic activity/energy supply system/energy demand/land use change/carbon absorption, yields and food demand and supply		Mori (1995)
MARKAL	policy optimization	Fishbone, L. G., and Abilock, H	Global	Energy/technology cost	ETSAP-TIAM, TIMES	Loulou et al. (2004)
MERGE (Model for Evaluating Regional and Global Effects of GHG Reductions Policies)	policy evaluation	Stanford University	Global	Global 2200/climate submodel/damage assessment submodel		Manne et al. (1995)
MESSAGE (Model for Energy Supply Strategy Alternatives and Their General Environmental Impact)	policy optimization	International Institute for Applied Systems Analysis	13 regions①	Simulation model/econometric model/ economic model/optimization model		Messner and Schrattenholzer (2000)
MIND (Model of Investment and Technological Development)	policy optimization	Potsdam Institute for Climate Impact Research	Global	Energy system/climate module/climate change damages		Edenhofer et al. (2005)
MS-MRT (Multi-Sector, Multi-Region Trade Model)	policy evaluation	IEA	10 regions①	CGE model		Bernstein et al. (1999)
PAGE (Policy Analysis of the Greenhouse Effect)	policy evaluation	Cambridge Judge business school (Chris Hope)	4 regions①	Temperature rise/global warming impact/ costs of implementing adaptive and preventative policies		Hope et al. (1993)
RAINS (Regional Air Pollution Information and Simulation)	–	IIASA[6]	–	Emission generation/emission control options and costs/atmospheric dispersion of pollutants/environmental sensitivities		Schöpp et al. (2005)
RICE (Regional Integrated model of Climate and the Economy)	policy optimization	William Nordhaus, Yale University	10 regions①	Emissions/concentrations/climate change/ damages/emissions controls		Nordhaus and Yang (1996)
SEAMLESS-IF (System for Environmental and Agricultural Modelling: Linking European Science and Society)	policy evaluation	SEAMLESS Association	Global	Agriculture production and externalities simulator (APES), farm simulation model (FSSIM), extrapolation and aggregation model (EXPAMOD), market model (SEAMCAP)		http://www.seamless-ip.org/
SIAM (Structural Integrated Assessment Model)	policy optimization	Pacific Northwest National Laboratory	Global	Carbon cycle model/climate model/ economic climate damage and greenhouse gas abatement costs		Hasselmann et al. (1997)
SGM (Second Generation Model)	policy optimization	Pacific Northwest National Laboratory	Global	CGE model		Sands (2004)
WIAGEM (World Integrated Assessment General Equilibrium Model)	policy evaluation	German Institute for Economic Research	25 regions①	economic, energy and climatic modules		Kemfert (2002)
WORLDSCAN	policy evaluation	Netherlands Bureau for Economic Policy Analysis (CPB)	Global	CGE model, energy system, damages of climate change		Bollen (2015)

[1] National Institute for Environmental Studies in collaboration with Kyoto University.
[2] Mizuho Information Research Institute and several research institutes in the Asia-Pacific region.
[3] National Institute of Public Health and Environmental Protection.
[4] Australian Bureau of Agricultural and Resource Economics and Sciences.
[5] Centre for International Research of Environment and Development.
[6] International Institute for Applied Systems Analysis.
① The IAM has divided the world into several regions.
② The IAM hasn't cover the whole world and just focused on several regions.

synthetically used with IAMs to deal with the uncertainties. (v) There are four parameters frequently discussed in samples, which are elasticity of the marginal utility of income or consumption (μ), pure rate of time preference (PRTP, ρ), equity weight (EW) and climatic sensitivity (CS). Researches on SCC are generally focused on the intergenerational discount rate, which consists of time discount and growth discount (Nordhaus, 1980). The discount rate (r) in IAMs is calculated based on Ramsey rule, which can be expressed as follow.

$$r = \rho + \mu \times g \qquad (2)$$

where g is the growth rate of income or consumption. The value of r is always one of focus of controversy in IAMs.

Furthermore, early studies often ignored regional equity and uncertainties when estimating SCC, while IAMs such as DICE/RICE, PAGE and FUND are more frequently applied in recent studies, studies consider these two factors combining the Monte Carlo method. These parameters are all used as quality indicators. In addition, dummy variables are adopted here to distinguish the studies which use DICE/RICE (model1), PAGE (model2), FUND (model3). Then it helps explore whether models have an influence on the estimated SCC. Accordingly, Table 4 shows statistic description of above selected characteristics of the whole samples.

Table 3
Specific modules and uncertainties of each IAM.

Model	Database	Carbon cycle	Climate model	Socioeconomic model	Uncertainties	References
AIM	GTAP database	energy end-use; land-use	GCM	Costs of damages of primary production (water supply, agricultural production, wood supply, etc) from higher temperature	Climate sensitivity	Matsuoka et al. (1995)
ASF	Various sources	–	–	It is a tool for estimating future GHG emissions	–	Leggett et al. (1992)
CETA	Energy Modelling Forum[1]	energy	GCM	costs of damage from and adaptation to higher temperature	Climate sensitivity, non-market damages, the rate of growth of labour input in efficiency units, the cost of the (carbon free) non-electric backstop technology	Peck and Teisberg (1992)
CLIMPACTS	–	MAGICC	GCMs	Costs of damages of crop from climate change (crop-weather model)	–	Peck and Teisberg (1992)
DEMETER	ERA-40 database	7 global coupled ocean-atmosphere models		Climate conditions change—agriculture (crop yield model)	Connections of 7 models	Warrick et al. (2001)
DICE	Various sources	Three-reservoir model	Equilibrium temperature as function of RF	costs of damage from and adaptation to higher temperature	of virtually all components from economic growth to damages	Nordhaus and Sztorc (2013)
DNE21	Various sources	MAGICC		Energy (MARKAL model)/Macro-economic model	Intergenerational discount rate	Fujii and Yamaji (1998)
DEARS	GTAP database	–	–	GTAP model	–	Homma (2013)
ENTICE	Energy data, DICE dataset	Three-reservoir model (DICE)	Equilibrium temperature as function of RF (DICE)	costs of damage from and adaptation to higher temperature	The opportunity cost of R&D, deviation between the private and social rate of return, decay rate, return to energy R&D, elasticity of R&D, exogenous reduction of carbon intensity	Popp (2004)
ESCAPE	Various sources	energy end-use; land-use; halocarbon	IMAGE and STAGGER	CLIMAPS	No interactions between different regions; simplified supply model; land-use model may not valid for individual countries; relationships between per capita income and consumption is uncertain; climate model is oversimplified.	Loulou (2008)
E3MG	energy/ emissions database	–	–	Economy/energy system	–	Dagoumas and Barker (2010)
FUND	Various sources	GHG concentrations model	one-box model and five-box model	costs of damage from and adaptation to higher temperature, damages of change of sea level	relative risk aversion, Inequity aversion, Intergenerational discount rate	Tol (1997)
G-CUBED/ MSG3	input-output data	–	–	Macroeconometric system	–	McKibbin and Wilcoxen (1999)
GCAM	Various sources	MAGICC	Equilibrium temperature as function of RF	Edmonds-ReillyBarns Model	climate sensitivity	Edmonds et al. (1997)
GIM	economic data	AOGCM(Atmosphere-Ocean General Circulation Models)		cross-sectional model and the experimental model	Socioeconomic models	Mendelsohn and Williams (2004)
GRAPE	EMF [1]	Three-reservoir model	–	Energy system	–	Kurosawa (2004)
GTEM	GTAP database	–	–	GTAP model	Limitations of emission coverage in GTEM	Tulpulé et al. (1999)
ICAM	Various sources	–	–	Energy system and GNP	Uncertainty on technical progress	Dowlatabadi (1998)
IGEM	input-output data	–	–	Production/household/investment/ government/rest of the world (export, import and total supply)/market balance	Future price and discount rates	Jorgenson et al. (2018)
IGSM	GTAP database	An ocean model with carbon cycle and sea-ice sub-models	An atmospheric dynamics, physics and chemistry model	EPPA	uncertainty in forecasts of future climate change, emissions projections, technical change	Reilly (2013)
IMAGE	Various sources	BernCC model	Pattern Scaling	GLOBIO model (biodiversity loss, human development)/health module	Uncertainty in future scenario drivers	Rotmans (2012)
IMACLIM-R	GTAP database	–	–	Producers/consumers/investment allocation/international markets/statistic equilibria	–	Crassous et al. (2006)
MADIAM	Various sources	NICCS (a Nonlinear Impulse-response representation of the coupled Carbon cycle-Climate System)		multi-actor dynamic economic model (MADEM); costs of damage from and adaptation to higher temperature, costs of higher dykes through sea level rise	investment coefficients, carbon and energy efficiency, human capital, climate damage coefficient	Weber and Hasselmann (2005)
MAGICC	Various sources	Six-reservoir model	energy-balance model	–	–	Meinshausen et al. (2011b)
MARIA	Various sources	Three-reservoir model		costs of damage from and adaptation to higher temperature	limited technology options	Mori (1995)

Table 3 (*continued*)

Model	Database	Carbon cycle	Climate model	Socioeconomic model	Uncertainties	References
			Equilibrium temperature as function of RF			
MARKAL	IEA, technology cost	–	–	Energy system	technology cost	Loulou et al. (2004)
MERGE	Various sources	impulse response function	Equilibrium temperature as function of RF	costs of damage from and adaptation to higher temperature	climate sensitivity	Manne et al. (1995)
MESSAGE	input-output data	–	–	Abatement technology	–	Messner and Schrattenholzer (2000)
MIND	Various sources	CO_2 and sulphate aerosols	energy-balance model	Energy system, R&D sector; costs of damage from and adaptation to higher temperature	technology cost	Edenhofer et al. (2005)
MS-MRT	GTAP4 dataset	–	–	production, household behavior, consumer choice, international trade, savings and investment, and carbon restrictions	–	Bernstein et al. (1999)
PAGE	Various sources	Pulse-response function	Equilibrium temperature as function of RF	costs of damage from and adaptation to higher temperature	climate sensitivity; economic impact weight	Hope et al. (1993)
RAINS	Various sources	Pulse-response function	Equilibrium temperature as function of RF	–	–	Schöpp et al. (2005)
RICE	Various sources	Three-reservoir model	Equilibrium temperature as function of RF	costs of damage from and adaptation to higher temperature	of virtually all components from economic growth to damages	Nordhaus and Yang (1996)
SEAMLESS-IF	GTAP database	–	Equilibrium temperature as function of RF	APES, FSSIM, EXPAMOD, SEAMCAP	Connections among different models	http://www.seamless-ip.org/
SIAM	Various sources	Three-reservoir model	global temperature response model	costs of damage to higher temperature	Discount rate for mitigation cost and climate damage cost	Hasselmann et al. (1997)
SGM	input-output data	–	–	production, household behavior, consumer choice, international trade, savings and investment, and carbon restrictions	technology cost	Sands (2004)
WIAGEM	GTAP database	–	MERGE 4.0	costs of damage from and adaptation to higher temperature, costs of higher dykes through sea level rise	climate sensitivity	Kemfert (2002)
WORLDSCAN	GTAP database	–	–		technology cost	Bollen (2015)

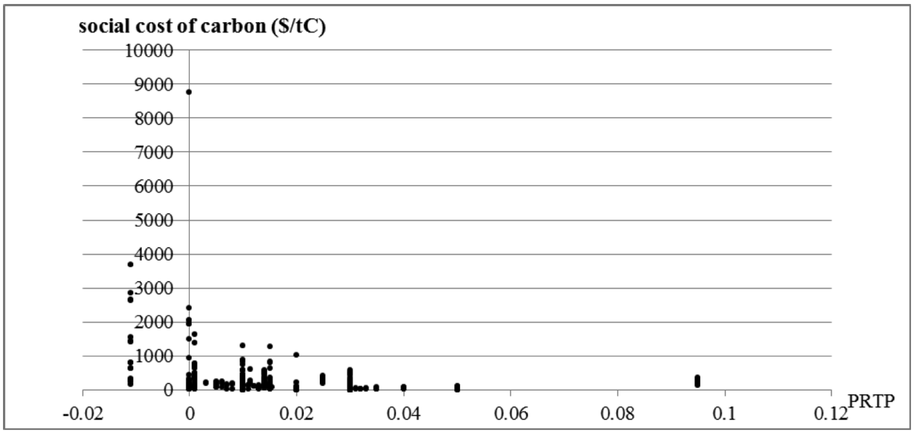
[1] Energy Modelling Forum, Study Design for EMF. The EMF study did not specify a total world coal resource base. We use an estimate obtained from Fulkerson et al. (1990).

4.2. Meta-analysis on the SCC

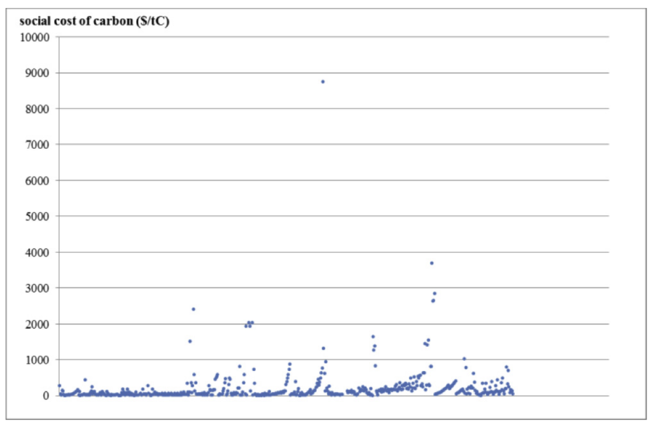
As shown in Fig. 5 (B), there is a large gap among the estimated SCC values from different studies, ranged from −50 to 8752$/tC (−13.36–2386.91$/tCO_2). On average, the estimated SCC is 200.57$/tC (54.70$/tCO_2), and it is 112.86$/tC (30.78$/tCO_2) with a PRTP at 3% in peer-reviewed studies. Estimated SCC in collected studies seems a little higher than that of the estimation by DICE on

Table 4
Description and summary statistics of SCC.

Variables	Description	Obs.	Mean	Std.Dev
year	Publication year of the study	578	2007.80	5.54
SCC	The estimated SCC reported in each studies (unit: $/tC)	578	200.57	514.82
PR	= 1 if the article is peer-reviewed	578	0.58	0.49
IE	= 1 if the article is independent estimate	574	0.67	0.47
RS	= 1 if the article set realistic scenario	500	0.97	0.18
ToU	= 0 if the estimation doesn't consider uncertainty; = 1 if the estimation consider the uncertainty and the method is not clear; = 2 if the estimation consider the uncertainty and variability; = 3 if the estimation consider the uncertainty and stochasticity	469	1.27	0.84
μ	Elasticity of the marginal utility of income or consumption	469	1.11	0.72
ρ	Pure rate of time preference (%)	564	0.019	0.019
EW	= 1 if the estimation consider the equity weight	576	0.17	0.37
CS	Climatic sensitivity (temperature rising when CO_2 doubling)	561	2.90	0.57
t	Emission year	420	2045.19	44.53
model1	= 1 if the study uses DICE or RICE model to estimate SCC	578	0.43	0.50
model2	= 1 if the study uses PAGE model to estimate SCC	578	0.12	0.32
model3	= 1 if the study uses FUND model to estimate SCC	578	0.35	0.48



A



B

Fig. 5. Relationship between social cost of carbon and PRTP (A) and distribution of collected data of social cost of carbon (B).

Table 5
Chi-square test for SCC and the other indicators.

Indicator	Pearson chi-square value	p-value	Indicator	Pearson chi-square value	p-value
year	10000	0.00	EW	494.55	0.07
PR	520.84	0.01	CS	7300	0.89
IE	471.18	0.26	t	8400	0.00
RS	521.93	0.01	model1	531.73	0.01
ToU	1400	0.01	model2	503.01	0.049
μ	9900	0.00	model3	524.50	0.01
ρ	14000	0.00			

baseline scenario (18.6$/t$CO_2$), but it matches the results conditional on 2 °C target (47.6$/t$CO_2$). The large gap is comprehensively influenced by the indicators listed in Table 4. Aside from these characters selected based on the literature review, chi-square test is conducted for SCC and the other characters (Table 5). P-value of Pearson chi-square implies that all the indicators in Table 4 are significantly connected with SCC except for IE and CS. However, Ackerman et al. (2013) indicated that SCC is 12.7 and 14.95 $/tC with climatic sensitivity of 3.0 and 3.55, respectively. Climatic sensitivity parameters are discussed in the estimation process in some studies. In sum, the default climatic sensitivity is 3 °C in DICE/RICE model, the PAGE model sets it as 3.5 °C when CO_2 doubling in the atmosphere, and this key parameter is 2.5 °C in FUND model. Thus, CS is still one of the key characteristics, which should be examined if it is correlated with the estimated SCC collected in the publications.

As shown in Table 6, the meta-regression to check for the relationship between estimated SCC and the publication characteristics of the studies has been presented. The results of the regression with estimated SCC, the logarithm of the estimated SCC, included IE and excluded IE are reported in each column. The R^2 value has indicated that the regression of the first and third column, which taken estimated SCC as dependent variable, perform better than that of in second and forth column. But the performance of each coefficient has suggested that the regression taken the logarithm of estimated SCC as explained variable seems much suitable. Moreover, chi-square test and the regression results of first and second column have implied that IE can be excluded for its weak correlation with explained variable and statistically insignificance. Thus, the regression for estimated SCC and the other publication features can be expressed as follow.

Table 6
Results of meta-regression: estimated coefficients and statistical significance.

Independent variables	Dependent variable			
	SCC	ln (SCC)	SCC	ln (SCC)
year	8.61 (6.54)	0.089*** (0.020)	9.62 (6.55)	0.088*** (0.020)
PR	95.22** (44.54)	0.27** (0.13)	112.40** (43.93)	0.26** (0.13)
IE	−101.98** (49.80)	0.060 (0.15)		
RS	−8642.20*** (328.44)	−4.69*** (0.96)	−8647.49*** (329.80)	−4.69*** (0.96)
ToU	69.56 (79.89)	−0.20 (0.24)	10.77 (74.87)	−0.17 (0.22)
μ	86.73*** (27.47)	0.22*** (0.081)	96.61*** (27.16)	0.21*** (0.079)
ρ	−5245.78*** (842.29)	−14.31*** (2.52)	−5071.67*** (841.48)	−14.46*** (2.49)
EW	−19.70 (51.21)	−0.18 (0.16)	−7.70 (51.09)	−0.19 (0.16)
CS	35.71 (32.59)	0.33*** (0.096)	54.38* (31.42)	0.31*** (0.091)
t	1.86*** (0.52)	0.011*** (0.0015)	2.42*** (0.44)	0.011*** (0.0013)
model1	45.27 (88.37)	0.53** (0.26)	95.95 (85.19)	0.50** (0.25)
model2	138.24 (98.06)	0.63** (0.29)	186.33** (95.60)	0.61** (0.28)
model3	−30.71 (102.43)	−0.22 (0.31)	50.59 (94.81)	−0.27 (0.28)
constant	−12428.2 (13505.33)	−192.24*** (40.50)	−15750.94 (13463.31)	−190.23*** (40.15)
R^2	0.69	0.52	0.69	0.52

$$\ln(\mathrm{SCC}) = -190.23 + 0.088 \times \mathrm{year} + 0.26 \times \mathrm{PR} - 4.69 \times \mathrm{RS} - 0.17 \times \mathrm{ToU} + 0.21 \times \mu - 14.46 \times \rho - 0.19 \times \mathrm{EW} + 0.31 \times \mathrm{CS} + 0.011 \times \mathrm{t} + 0.5 \times \mathrm{model1} + 0.61 \times \mathrm{model2} - 0.27 \times \mathrm{model3} \quad (3)$$

As shown in equation (3), the publication year is significantly related to the estimated SCC. It also indicates that the estimated SCC is larger when the study is newer, but this effect is marginal. One of the possible explanations is that the designed scenario is constantly improved, many studies are estimated not only based on the basic scenario, but also on the rapid economic growth scenarios. The second potential interpretation is that uncertainty analysis is often considered in the estimation in recent year, which tend to report a larger SCC. However, these two parameters perform statistically insignificant. But Schauer in 1995 reported that SCC increased from 8.27 to 112.5 on account of taking external uncertainty into consideration. Moreover, this result also implies that scientists have stronger crisis awareness from climate change recently.

The regression results also reported that peer-reviewed studies in our meta-analysis dataset on average have a lager SCC. Combined with Fig. 6 (B), outliers appear in studies haven't published on peer-reviewed journals. Accordingly, outliers are not the factor to affect estimated SCC. But one of the potential reasons for the statistical performance of PR is that most of the negative values of estimated SCC appear in the studies haven't published on peer-reviewed journals. As shown in Fig. 6 (A), all the outliers appear when the realistic scenario equals to zero, which is in line with performance of RS in equation (3), estimated SCC is smaller conditional on a realistic scenario.

Notably, PRTP and elasticity of the marginal utility of income or consumption are highly sensitive to the estimated SCC. According to Ramsey equation, these two variables are tightly associated with the intergenerational discount rate, which is one of the most important parameters to determine SCC. As expected, a larger PRTP leads to a smaller SCC, while a larger elasticity leads to a smaller SCC. As shown in Fig. 5 (A), PRTP is mainly ranged from 0% to 3%, consistently, the estimated SCC is higher with a lower PRTP. In accordance with the existing studies, the regression result about CS indicates that the higher the climatic sensitivity, the higher the estimated SCC. Similarly, if emission year is larger, the estimated SCC is higher. Finally, studies using FUND is not significant at 10% level, which has indicated that estimated SCC from FUND model is varying. Studies employ DICE/RICE and PAGE model are larger than that of the other models.

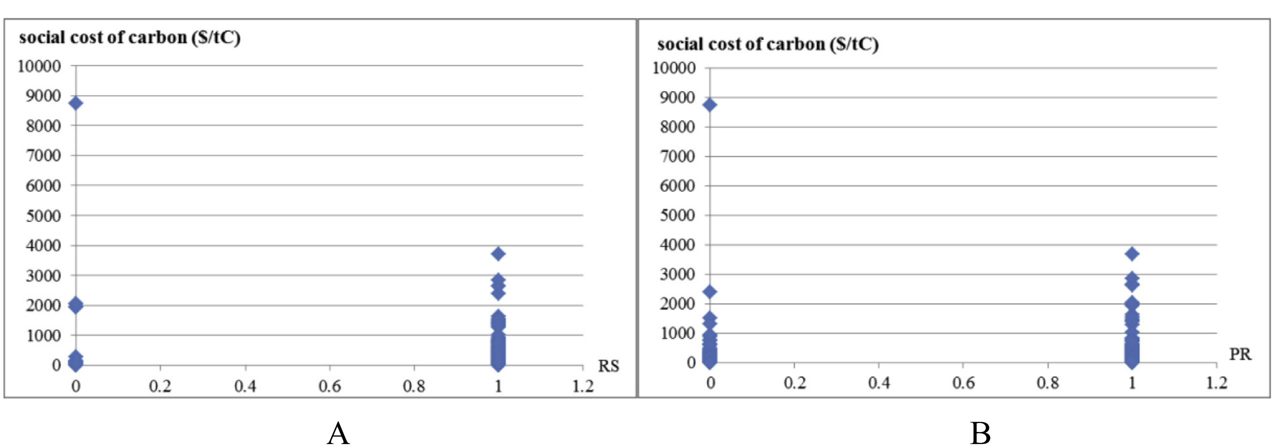


Fig. 6. Distribution of social cost of carbon and realistic scenario (A), social cost of carbon and peer-reviewed study (B). Note: RS = 1 if the study estimates SCC based on the realistic scenario, PR = 1 if the study has publish in peer-reviewed journal.

5. Conclusions and discussion

5.1. Conclusions

Our study mainly had a literature review on the internal mechanism and structure of IAMs, and simultaneously, a list of current IAMs were presented as far as possible. With the basic knowledge on these models, the studies on the estimation of SCC were collected and its characteristics were summarized to establish a raw dataset for meta-analysis. It has 578 estimates of SCC from 58 studies, many of which have multiple results of estimated SCC. These studies provided a wide variety of the estimated SCC with different values of key parameters, different methods or IAMs for estimation. In all collected data, the estimated SCC ranged from −50 to 8752\$/tC (−13.36–2386.91\$/tCO_2), with a mean value of 200.57\$/tC (54.70\$/tCO_2). Specifically, it equaled to 112.86\$/tC (30.78\$/tCO_2) with a PRTP at 3% in peer-reviewed studies. In the regression results, publication year, peer-reviewed studies, realistic scenario setting, elasticity of the marginal utility of income or consumption, PRTP, climatic sensitivity, carbon emission year, employment of DICE/RICE and PAGE model were all statistically significant with the estimated SCC. Aside from the realistic scenario setting and PRTP, the other indicators have a positive effect on estimated SCC. In addition, outliers in our study appeared without a realistic scenario setting or studies not in peer-reviewed journals. Practically, the high value of the estimated SCC presented that damages from climate change was enormous, the most useful measures for mitigation was carbon reduction, including the improvement on energy use efficiency and forestry protection.

5.2. Discussions

Comparatively, the publication year and peer-reviewed studies in regression performed opposite to the results of meta-analysis from Tol. It indicated that our dataset was selective, not included all the researches related with SCC. In order to extract more information, studies only containing estimated SCC and repeated results were all eliminated, then 58 studies selected from 172 literature. Furthermore, variables in Table 5 were selected based on the current research and our meta-regression did not include all variables because of large deficiencies in the datasets of some variables. For example, the driving gases, regional scale in estimation, catastrophic events and so on.

Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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